Landslides
DOI 10.1007/s10346-016-0775-6
Received: 16 March 2016
Accepted: 31 October 2016

Tonje Grahn · Henrik Jaldell

Assessment of data availability for the development of landslide fatality curves

Abstract Quick clay landslides are a special feature of Norwegian and Swedish geologies. Vibrations or small initial landslides can cause a quick clay layer to collapse and liquefy, resulting in rapid landslides with little or no time for evacuation, making them a real threat to human life. Research concentrating on damages due to landslides is scarce, and analyses of loss of human lives caused by quick clay landslides in the scientific literature are, to our knowledge, non-existing. Fatality quantification can complement landslide risk assessments and serves as guidance for policy choices when evaluating efficient risk-reducing measures. The objectives of this study were to assess and analyze available damage information in an existing data set of 66 historical landslide events that occurred in Norway and Sweden between 1848 and 2009, and access its applicability for quantifying loss of human life caused by quick clay landslides. Fatality curves were estimated as functions of the number of exposed persons per landslide. Monte Carlo simulations were used to account for the uncertainties in the number of people actually exposed. The results of the study imply that the quick clay fatality curves are non-linear, indicating that the probability of losing lives increases exponentially when the number of exposed persons increases. Potential factors affecting human susceptibility to landslides (e.g., landslide-, area-, or individual-specific characteristics) could not be satisfyingly quantified based on available historical records. Future research should concentrate on quantifying susceptibility factors that can further explain human vulnerability to quick clay landslides.

Keywords Landslide · Quick clay · Loss of life · Landslide fatalities · Data availability · Landslide damage

Introduction

In a wide context, natural hazards impose a real threat to human life all over the world. From 1994 to 2013, the average death toll was greater than 99,700 per year (Cred 2015). Statistics from The Center for Research on the Epidemiology of Disasters (CRED) show that 17% of all fatalities from natural hazards worldwide were caused by landslides (Lacasse et al. 2010). In contrast to other natural hazards (e.g., floods or earthquakes), which affect large areas, landslides are generally limited in area but can occur with a high frequency in a specific region (JRC 2011). Landslides can be caused by both natural and anthropogenic actions, and landslide disasters are increasing worldwide (Andersson-Sköld et al. 2014; Guzzetti 2016; Ho et al. 2013; Nadim et al. 2006; SOU 2007). The reasons are suspected to be increased susceptibility of surface soil to instability because of deforestation and overexploration of natural resources, greater vulnerability of exposed population as a result of urbanization and uncontrolled land use, and climate change resulting in a greater potential for weather extremes (Lacasse et al. 2010; Nadim et al. 2006). Pereira et al. (2014) have found that most landslides occur during the wettest months, reflecting the importance of rainfall-triggering mechanisms. Landslides can cause serious damage to buildings and infrastructure, to the environment, and to human life (Devoli et al. 2007; Jiménez-Perálvarez et al. 2009; Lacasse et al. 2010). Further, landslides in populated areas can create health consequences that exceed the local capacity to respond, increasing both mortality and morbidity from disasters (Keim 2008). These types of disaster risks therefore need to be taken into account in present and future societal planning at local, regional, and national levels.

Quantifying the consequences can assist the risk management process by guiding policy interventions to choose the most effective mitigation project. This evokes a large demand from policy makers on local, regional, and national levels for quantitative damage estimates as guidance and support so that efficient decisions can be made in the use of public and private resources for risk-reducing measures. Quantification of loss of life or injuries are however problematic because information often is incomplete.

The main scope of landslide hazard assessments is to provide quantitative expertise on future slope failures to planners, decision-makers, civil defense authorities, insurance companies, developers, and individual landowners (Guzzetti et al. 2005a). Within the field of risk assessment, methods for estimating hazard probabilities are relatively well-established, but when determining risks related to natural hazards, many studies neglect investigating the damage potential or are limited to the assessment of immobile objects such as buildings (Jonkman et al. 2010). Landslide risk (R) is usually described as a function of probability and the consequences of a landslide (e.g., Andersson-Sköld et al. 2014)

$$R = P \times C_i$$

where P is the probability of a hazard, and $\boldsymbol{C}$ is a vector C_i of all potential consequences. Fatalities (C_f) can then be expressed as a function of human susceptibility (S_f) to landslides when exposed and the number of exposed humans (E).

$$C_f = S_f \times E$$

The largest proportion of landslide risk analyses or landslide susceptibility analyses has had a technical approach focusing on the first part of the function, the hazard probability (P), by performing and developing methods for mapping landslide risk, stability analysis, and mechanisms triggering landslides (e.g., Guzzetti et al. 2005a, 2006, 2012; Jiménez-Perálvarez et al. 2009; Melchiorre and Tryggvason 2015; Poli and Sterlacchini 2007; Roslee and Jamaluddin 2012; Salas-Romero et al. 2015; Van Den Eeckhaut et al. 2012). Potential landslide consequences (C_i) have not attained the same scientific interest despite the obvious importance it has on the estimated risk product (R). Further,

Published online: 16 November 2016

estimations have been found to be more sensitive to uncertainties in damage susceptibility (S) than uncertainty in hazard exposure (P) (Jongman et al. 2012).

Few published studies address quantitative landslide analysis of consequences (C_f) to human life. Among the scientifically published literature, an extensive portion focuses on Italian landslide scenarios. Several studies base their research on variations of the same historical landslide catalogs (e.g., Guzzetti et al. 2003, 2006; Salvati et al. 2010). Analyses of experienced risk factors affecting fatality rates can, however, serve as input to risk assessments and disaster response by increasing the understanding of vulnerable groups and ease assistance in the direct aftermath of a disaster (Agrawal et al. 2013). Previous studies have shown that historical information from landslides can be valuable when quantifying landslide threat to human lives (Cascini et al. 2008).

This study analyses consequences of quick clay slides by focusing on exposure (E), and human susceptibility (S_f) to loss of life.

$$R_f = P \times (S_f \times E)$$

The objective of this study is to assess available damage data from previous quick clay landslides in order to identify and quantify factors affecting human susceptibility to landslides. Fatality functions are derived and compared to fatality rates previously applied in risk assessment for policy purposes. We will use data from the Swedish Geotechnical Institute (SGI 2011, 2012). To our knowledge, the Göta River investigation is the only investigation thus far that included quantification of the loss of human life from landslides in the Nordic countries. However, the fatality rate is burdened with large uncertainties due to uncertainties in the number of exposed humans (E). It is therefore interesting to perform a more in-depth analysis of the estimations of loss of life using this data set.

Landslide characteristics and methods for quantification

Experienced fatalities in European landslides

Fatality numbers and fatality rates vary between countries and regions. Landslides differ in their characteristics, such as temporal perspectives and warning opportunities. Since European landslides often are small, isolated events, this leads to an underestimation of European landslides reported to global databases (Van Den Eeckhaut et al. 2012). For example, EM-DAT reports landslide events where more than 10 people were killed, 100 or more were affected, or international assistance or a state of emergency were called for (Van Den Eeckhaut et al. 2012). Based on the Northern Portugal Landslide Database (NPLD), 136 people lost their lives in 436 landslides between 1900 and 2010 in Portugal (Pereira et al. 2014). This yields an average fatality rate of 0.3. In Switzerland, Hilker et al. (2009) found by assessing The Swiss Federal Research Institutes (WSL) landslide database, that fatalities averaged 3 per year during the time period 1972–2007. Three hundred forty-four landslides occurring in the Umbria region in Italy between the years 1941 and 1997 caused 12 fatalities, yielding an average fatality rate of 0.03 (Guzzetti et al. 2006). A national Italian investigation on landslide risk in the twentieth century revealed that at least 7799 casualties were reported, 5831 lives were lost, 108 missing, and 1860 injured (Guzzetti et al. 2003). Extending the time period to the years 1279–2002 and including landslides causing death, missing people, injuries, and homelessness, landslides caused a total of 10,111 fatalities yielding and average fatality rate of 10.1 (Guzzetti et al. 2005b). This data set includes the disastrous landslide at the Vajont dam in 1963 that generated an enormous wave, killing almost 2000 people. Guzzetti (2000) found that the national landslide mortality rate in Italy decreased between 1950 and 1999. Compared to other areas, the fatality frequency was found to be lower in the Alp region, Canada, and Hong Kong, but higher in Japan and China (Guzzetti 2000). Giannecchini and D'Amato Avanzi (2012) found that, in the Versilia River Basin, landslides and flood together caused between 1 and 13 fatalities per event.

Considering the Nordic countries, approximately 2000 people have been killed by all kinds of landslides in Norway (Jaedicke et al. 2009) during the last 150 years. No such compilation has been performed for Sweden, but since 1950, at least 10 people have lost their lives, and 160 were injured as a result of landslides (MSB 2016).

Factors affecting susceptibility (S_f)

Damage caused by landslides mostly affects private homes, road networks, and other infrastructure (Guzzetti et al. 2006). This is where humans are most likely to get exposed to landslides. Fast-moving landslides, including rock falls, rockslides, rock avalanches, and debris flows, have historically caused the largest number of landslides deaths (Guzzetti 2000). The threats that landslides induce on human life are often a main concern. Humans are an essential part of the damage potential because landslides are associated with high rates of traumatic injury and mortality caused by trauma and suffocation (Keiler et al. 2005; Keim 2008). Research quantifying risks to human lives when exposed to landslides do exist, but is not extensive. Agrawal et al. (2013) examined landslides in Uganda and focused on risk factors affecting the extent of impact to human life and health. Despite the differences between Uganda and the Nordic countries in terms of factors such as socioeconomic aspects, the risk factors identified in that study are of interest. The following risk factors were assessed: number of exposed individuals, sex, age, type of injury, severity of injury, type of medical assistance, and where the injury occurred (e.g., at home, inside, outside, or in a vehicle). The study also showed that in Uganda, most people are injured or killed outside and not at their place of residence. This diverges from the data describing Norwegian quick clay landslides, where loss of life occurred most frequently in the person's place of residence (Jaedicke et al. 2009). Zhang and Zhang (2014) examined factors involved with human flight behavior related to rapid landslides along roads in China. They showed that the susceptibility of humans when exposed inside buildings depends on the characteristics of the landslide and the technical resistance of the buildings, but also that individual behavior and personal attributes (i.e., age, sex, disability, running speed, response, education, and prior experience with landslides) are of large importance for successfully fleeing a landslide. People with reduced health statuses are also more vulnerable when exposed to disasters (Keim 2008). Personal attributes being an important factor for human susceptibility are confirmed by Viscusi (2006) claiming that the magnitude of loss of human life is influenced by factors such as individuals' exposure to hazards and their levels of self-protective behavior. Lacasse et al. (2010) further points out that day of week, time of day, and functioning warning systems are risk factors that should be taken into account. Furthermore, healthy people are less likely to suffer disaster-related mortality and are therefore more disaster resilient (Keim 2008).

Susceptibility to flood exposure is also relevant to consider since landslides near rivers, lakes, and coasts can be flooded when large amounts of soil and clay slide into the water, creating large waves rapidly flooding the surrounding areas with risk to human life, livestock, and other asset values.

Methods for quantifying fatalities (C_f)

General methods for estimating consequences such as loss of life have not been standardized to the same extent as estimations of hazard probabilities (Jonkman et al. 2010). Jonkman et al. (2010) presented a general approach for estimating loss of life for “low probability-large consequence” accidents and disasters. This general approach includes an assessment of physical effects associated with an event, determination of the number of exposed persons, and determination of the mortality among the exposed population.

Previous scientifically published quantification on fatalities are, as far as we know, calculated frequency rates for average number of fatalities per event, year, month, day, intensity, area of occurrence or expressed as the number of deaths per 100,000 inhabitants for a given population over a predefined time period (Cascini et al. 2008; Giannecchini and D’Amato Avanzi 2012; Guzzetti et al. 2005b; Hilker et al. 2009; Pereira et al. 2014; Salvati et al. 2010). Methodologically, the studies differ concerning which observation inclusion criteria that are used when deriving a fatality (or mortality) rate. Guzzetti et al. (2005b) combined the number of missing people with the number of deaths when estimating fatalities. Salvati et al. (2010) also included injured humans as well as those killed and declared missing. Giannecchini and D’Amato Avanzi (2012) did not distinguish between flood and landslide fatalities. The studies also differ in the length of time periods used for estimating a landslide fatality rate. Guzzetti et al. (2005b) includes information from landslides going back to 1279, and Salvati et al. (2010) as far back as year 68. How well the oldest landslides reflect present human susceptibility to landslides is questionable.

Salvati et al. (2010) also performed a more detailed risk evaluation for Italy for the time period 1950–2008. They compared magnitude of events between regions and time periods by modeling distributions of flood and landslide events with causalities taking into account the frequency and intensity of events. They performed the analysis using a Zipf distribution which is a discrete distribution often used for modeling rare events for a finite population size. The analysis performed by Salvati et al. (2010) requires an abundant amount of data. This is available in Italy since Italy has access to more data, due to that the country has suffered substantial losses to landslides, has a strong tradition of historical research, and that an extensive part of the landslide damage literature stems from Italian research groups.

To increase the knowledge of the risk of landslides in Sweden, the Swedish Geotechnical Institute (SGI), at the Swedish government’s initiative, performed comprehensive risk analyses of landslide risks in the Göta River valley. The main focus was on hazard events (i.e., stability analysis), but a large proportion of the analyses was also dedicated to identifying, quantifying, and, as far as possible, monetizing potential future damage from landslides (Göransson et al. 2014; SGI 2012). SGI developed a method for quantifying risk of losing lives and add this type of consequence to other types of consequences (i.e., building, infrastructure, and industrial damage, etc.). A prerequisite for applying the method is to quantify human susceptibility when exposed to landslides (C_f). C_f was calculated as the relative frequency of fatalities and exposed population (evacuated population not included) using historical records (SGI 2011).

Characteristics of quick clay landslide

Quick clay landslides occur in Norwegian and Swedish geologies where large land areas with quick clay deposits are seen (Jaedicke et al. 2009; SGI 2012; Salas-Romero et al. 2015). Quick clay can develop both in marine and fresh water sediments, but most Scandinavian quick clay developed in glaciomarine sediments deposited during deglaciation 14,000 to 10,000 years ago (Salas-Romero et al. 2015). Quick clay is a soil with high water content and weak binding between the particles (Andersson-Sköld et al. 2014). Vibrations or small initial landslides can cause a quick clay layer to collapse and liquefy, resulting in rapid landslides (Andersson-Sköld et al. 2011). This can be caused by natural processes (e.g., precipitation and/or erosion) or by human processes (e.g., overloading and excavation) (SGI 2012). Quick clay landslides occur without warning signs leaving little or no time for warning and evacuation (Melchiorre and Tryggvason 2015; SGI 2012). Signs of creep have, however, on some occasions been documented prior to landslides (Melchiorre and Tryggvason 2015). Quick clay landslides occur in Norway and Sweden on a regular basis and become hazardous events when they occur in developed and populated areas. Large quick clay landslides in populated areas are not frequent in Scandinavia, but areas are continuously being mapped because of the concern about potentially large and unacceptable consequences. One example is the most landslide prone area in Sweden, the highly developed and populated Göta River valley, with a number of landslides every year (Andersson-Sköld et al. 2014). However, because of the low frequency of large quick clay landslides, area-specific data available for damage analyses and damage prognoses are scarce.

Data and methods

Sample data set

In this study, we analyze the data set compiled by the SGI for use in landslide risk assessment of the Göta River valley. The data set has in the present study been subject to content analysis in order to identify susceptibility factors (S_f) and other quantitative damage information identified as relevant by previous research (see “Landslide characteristics and methods for quantification” section) and to analyze the uncertainty of the derived susceptibility factor. The data set contains 66 landslides collected from two data sources. Among them, 55 quick clay landslides that occurred between 1848 and 2009 were extracted from the Norwegian landslide database, Skrednett. The data quality related to documentation of historical events is strongly influenced by the personal engagement of local observers and observational routines. (Jaedicke et al. 2009). Despite the uncertainties, the database is seen as a unique source for statistical analysis, including risk analysis (Jaedicke et al. 2009). The remaining 11 landslides were extracted from the Swedish natural hazards information system and occurred in Sweden during a shorter time period, 1950 to 2006 (MSB 2016). The landslide frequencies differ between Norway and

Sweden. While the frequency of landslides in Norway is approximately the same as for Austria and Italy, it has been lower in Sweden which has the same frequency as Switzerland (Andersson-Sköld et al. 2013).

We have been looking at the characteristics describing exposure and vulnerability in the specific landslide events in the data set that could have been affecting human susceptibility in these events, and evaluating the potential for quantification of the characteristics.

Exposure and fatalities

Fatalities per landslide ranged from 0 to 116. Overall, 167 people lost their lives in the 66 landslides, yielding an average landslide fatality rate of 2.5 (Table 1). Humans were exposed in only 52 to 62% of the landslides, and people died in 27% of them, meaning that many events resulted in zero people exposed and zero fatalities. Exposed persons ranged from 0 to 375 per landslide. Because of uncertainties in the data set concerning the actual number of people exposed per landslide, the number of exposed humans is represented by an interval for some landslides. The number of people exposed overall, summing up all the landslides in the sample is between 734 and 1594. Where human exposure was burdened with uncertainty and therefore given as an interval, the SGI gave a *best guess* and used this as a point estimator together with other certain observations to derive an average fatality rate (C_f). Combining the sum of these *best guesses* for number of people exposed (1035) with the total 167 fatalities produced an average fatality rate of 0.161 and was applied in the governmentally initiated risk assessment representing human susceptibility of people potentially exposed to future landslides in the Göta River Valley.

The data shows that humans were exposed in 34 events, and for 13 events, it described non-fatal injuries, from minor to severe and irreversible. For two events, humans did not suffer physical damage, but in one, a victim was not able to escape because of a physical disability. Summarizing the fatal landslides, they have the following distribution: In 7 landslides, one died; in 2 landslides, three died; in 4 landslides, four died (Fig. 1); there were one landslide each with six, seven, eight, and nine fatalities. Concerning number of fatalities, one landslide event stands out. This is the Verdal landslide in Norway in May 1893. It occurred at nighttime in Verdal in Northern Tröndelag killing 116 persons of the 250 persons exposed to the landslide.

The data set also documents eight landslide events near lakes and rivers causing flood exposure to nearby settlements resulting in a range of poorly documented tangible damages.

Warning signs and previous experience

For 29 events, some kind of warning signal (e.g., gliding, creep, cracks, sinking of the ground, or small initial landslides) had indicated that a landslide was underway (Table 1). Anecdotal descriptions could be found, such as the detection of a crack in a window observed prior to the landslide that demolished the house. The crack was in the aftermath of the slide interpreted as signs of soil instability affecting the structure of the house. For two events, residents in the area saw the landslide coming and were able to escape to safety. Further, 16 events occurred in areas previously exposed to landslides.

Time of occurrence

Other characteristics interesting to quantify is time of occurrence. For all events, the year of occurrence was recorded but the month was recorded for only 59 events, and in 3 others, only the season was recorded. For 31 events, the accurate time of day was recorded, but for 17, it was recorded only as day or night. For the remaining slides (42%), the time of day is unknown. Of those slides for which the time of day was recorded, 13 slides occurred during the night. These landslides exposed a total of eight humans and caused the loss of six lives (Table 1).

Statistical methods

While the data presented in "Sample data set" section can serve as a basis for identification of risk factors, it is of utmost importance that the amount of data is sufficient relative to the number of parameters in a model (Jonkman et al. 2010). The amount of available data determines the detail level in the model used for estimation. Country, year, and number of people exposed were the only potential risk factors in the sample set adequately documented to serve as input data to the statistical analysis estimating the loss of life functions. Further, the 26 landslides where humans definitely were not exposed were dropped from further consideration in the statistical analysis. Two statistical approaches were applied to the remaining data set. (1) Regression analysis was used to explore the relationship between fatalities and number of exposed humans, country of occurrence and year of occurrence, under the hypothesis that number of persons exposed per landslide, country of occurrence and year of occurrence affect the number of fatalities per landslide. (2) Monte Carlo simulation was performed to take the uncertainty in the relative frequency of landslide fatality rates as a function of the number of exposed humans per landslide into account.

Regression analysis

Two different types of regression models are applied to the data set. One linear model using ordinary least squares (OLS) and one non-linear count data regression analysis applying two different distributions. The models have all been estimated using one dependent variable (the number of fatalities) and three independent variables (country [Norway or Sweden], year, and number of people exposed based on SGI's *best guess* values). Because the Verdal landslide is a statistical outlier, the models were estimated both with and without it. The estimated function for the linear model is given by the following:

$$\text{Fatalities} = \beta_0 + \beta_1 \times \text{Number Exposed} + \beta_2 \times \text{Norway} + \beta_3 \times \text{Year}.$$

Count data models were applied because of the properties of the fatality variable. The values for fatalities are discrete, have relatively low numbers, and include zeros. The tested count data models were the Poisson model and the negative binomial model.

Table 1 Overview of the data set by country, county, year, month, and time of occurrence, number of exposed humans, number of fatalities, injuries, cause of landslide, warning signs, prior slide in the area, and if a landslide triggered a flood damaging wave. Empty spaces in the columns means that the information is unknown and not documented in the databases

Number	Country	County	Year	Month	Time of day	Exposed humans	Fatalities
1	Norway	Trondheim	1848	September	03.00	3	1
2	Norway	Nord-Tröndelag	1859	September	Daytime	2	0
3	Norway	Sör-Tröndelag	1871	December	Daytime	4	0
4	Norway	Nord-Tröndelag	1874	April	Daytime	1	0
5	Norway	Akershus	1883	November	Nighttime	10	6
6	Norway	Nord-Tröndelag	1893	May	01.30	250	116
7	Norway	Troms	1898	December	05.00	12	7
8	Norway	Nord-Tröndelag	1900	May	Daytime	4	3
9	Norway	Nordland	1902	November	Daytime	12	4
10	Norway	Nord-Tröndelag	1909	July	Daytime	0	0
11	Norway	Sör-Tröndelag	1920	September	07.00	1	0
12	Norway	Nord-Tröndelag	1921	Springtime		1	0
13	Norway	Östfold	1925	April		0	0
14	Norway	Nordland	1925	July		0	0
15	Norway	Nordland	1925	April		2.5	0
16	Norway	Buskerud	1927	Mars		0	0
17	Norway	Nord-Tröndelag	1932	Mars		3	0
18	Norway	Buskerud	1935	January		6	4
19	Norway	Vestfold	1937	January	10.30	2	0
20	Norway	Telemark	1943	July		50	0
21	Norway	Akershus	1950	October		0	0
22	Norway	Akershus	1953	December	Nighttime	0	0
23	Norway	Nord-Tröndelag	1959	April	08.50	2	1
24	Norway	Nord-Tröndelag	1962	September	Nighttime	1–48	1
25	Norway	Sör-Tröndelag	1965	June		1	0
26	Norway	Nord-Tröndelag	1965	April		0–5	0
27	Norway	Nordland	1965	January		0–3	0
28	Norway	Östfold	1967	October	11.36	4–45	4
29	Norway	Sör-Tröndelag	1973	December		1	0
30	Norway	Östfold	1974	December	16.30	0–5	0
31	Norway	Telemark	1976			3	1
32	Norway	Sör-Tröndelag	1978	April	Daytime	1–40	1
33	Norway	Östfold	1980	August		0	0
34	Norway	Östfold	1980			0	0
35	Norway	Sör-Tröndelag	1982	March		0	0
36	Norway	Nord-Tröndelag	1982	October	Morning	0	0
37	Norway	Nordland	1984	July		0	0
38	Norway	Troms	1984	May	11.00	0	0
39	Norway	Sör-Tröndelag	1985	October	11.30	7	0
40	Norway	Östfold	1986			0	0

Table 1 (continued)

Number	Country	County	Year	Month	Time of day	Exposed humans	Fatalities
41	Norway	Sör-Tröndelag	1987	December		1–3	0
42	Norway	Östfold	1988	Springtime		0	0
43	Norway	Sör-Tröndelag	1989	November		1–3	1
44	Norway	Hedemark	1994	October	20.00	0	0
45	Norway	Nordland	1996	June	Nighttime	7	4
46	Norway	Hedemark	1999			0	0
47	Norway	Akershus	2000	November		0	0
48	Norway	Buskerud	2000	Autumn		1–13	0
49	Norway	Troms	2001	June		0	0
50	Norway	Sör-Tröndelag	2002	April	04.00	0–5	0
51	Norway	Nord-Tröndelag	2002	April	Nighttime	1	0
52	Norway	Nord-Tröndelag	2007	March	Daytime	0	0
53	Norway	Nord-Tröndelag	2007	May		0–5	0
54	Norway	Östfold	2008	April		0	0
55	Norway	Nord-Tröndelag	2009	March	11.50	7–100	0
56	Sweden	Västra Götaland	1950	September	08.00	90–375	1
57	Sweden	Västra Götaland	1953	April	14.00	0–6	0
58	Sweden	Västra Götaland	1957	June	11.25	6–310	3
59	Sweden	Värmland	1969	April	04.00	0	0
60	Sweden	Stockholm	1972	October	Nigttime	0	0
61	Sweden	Västra Götaland	1977	November	16.05	200	9
62	Sweden	Ångermanland	1987	November	Nighttime	0	0
63	Sweden	Västra Götaland	1996	April	18.40	0	0
64	Sweden	Södermanland	1997	May	00.59	10	0
65	Sweden	Örebo	2006	December	Morning	0	0
66	Sweden	Västra Götaland	2006	December	19.00	28	0

Number	Injuries	Cause of slide	Warning signs	Prior slides in area	Damaging wave
1				Yes	
2					
3			Yes, saw the slide coming		Yes
4	1				Yes
5		Rainy autumn	Initial slide 2 weeks earlier	Yes	Yes
6	Many injuries		Small slides occurring in the area during springtime, the river turned gray despite no rain	Yes	Yes
7			Several slides occurring in the area prior to the main slide	Yes	
8		Construction of railway, possibly caused by dynamite			
9	8	Construction of railroad			
10	0				
11	Light injuries	Construction			No

Table 1 (continued)

Number	Injuries	Cause of slide	Warning signs	Prior slides in area	Damaging wave
12					
13	0	Occurred after rainy period	Small initial slides led to evacuation of people and animals	Yes	
14	0			Yes	
15					
16	0				
17		Possibly the lowering of water levels in the river	People started running when land started moving		
18					
19					
20	Minor injuries	Bombing (WW2)			
21	0				
22	0		People used to landslides. Land movement detected the day before led to evacuation	Every year	
23	0	Erosion in river			
24					
25					Yes
26					
27					Yes
28		Rainy period	Land movement had been observed, and a crack in a window had also been observed		No
29					
30				Yes	
31					
32		Human element			Yes
33	0	Human element			
34	0				
35	0			Yes	
36	0			Yes	
37	0				
38	0				Yes
39	7 injured	Intensive rain might have triggered the slide			
40	0			Yes	
41	1	Heavy rain			
42	0	Probably water undermining the ground			
43	0	Probably triggered by heavy rain		Yes	

Table 1 (continued)

Number	Injuries	Cause of slide	Warning signs	Prior slides in area	Damaging wave
44	0				
45		Possibly road construction			
46	0			Yes	
47	0				
48					
49	0			Yes	
50	0	Land filling			
51					
52	0	Possibly triggered by road construction			
53		Erosion from the river Reina			
54	0	Potentially triggered by heavy precipitation			
55	Minor damages	Partly triggered road construction			
56	90	Pilework had been done a few days prior to the slide and the vibrations might have triggered the slide	Cracks where observed prior to the slide		
57	0		Slide	Yes	
58	3	Erosion of the river	Cracks where observed prior to the slide and led to evacuation of the area		
59	0	Erosion of the river	A sinking in the road had been observed the day prior to the slide		
60	0	Depositing of the soil on top of slope in combination with construction work			
61	60				
62	0	Probably erosion of the river			
63	0	Erosion in the river in the combination with low water levels			
64	5 minor injuries	Combination of erosion, development/exploitment, and rain	Minor slides had been observed in the area the week prior to slide	Yes	
65	0	Construction and rain	Sinking and gliding of soil in the area had been observed		
66	3 injured	Construction and rain			

The Poisson model assumes that the expected value and variance are equal. A negative binomial model takes into account that the variance is greater than the expected value (overdispersion). Overdispersion is estimated by a parameter alpha (see, e.g., Greene 2008). The count data models were compared using various test statistics using likelihood values, the Vuong test, and comparing the actual to the predicted probabilities following the procedures suggested by Long and Freese (2014). The count data model that best fit the data was the negative binomial regression model.[1]

Monte Carlo simulation

There are, however, two major drawbacks with using the ordinary least square model and the negative binomial model to the data set in this study. The first is that we have only 40 observations, which makes statistical inference difficult. The second is that there are uncertainties about number of people exposed, in some cases, a single number represents those exposed, but for others, a range is recorded.

By making Monte Carlo simulations with the data, it is possible to account for the uncertainties in the exposure variable. The Monte Carlo simulation was performed by simulating 1000 trials from each landslide.

To do so, we made assumptions about the statistical distributions of the uncertainty in the exposure variable based on information documented in the landslide databases. Four different distributions were applied. (1) If a single number represented those exposed, we assumed the value was certain, and it was used (no distribution). (2) If a particular value could be assumed to be more probable, but an interval surrounding this value also was given, we applied a triangular distribution covering the interval given but using the most probable value as the mode. (3) If the most probable value was zero, but there was uncertainty, we applied a right triangle distribution (skewed distribution). (4) If only an interval was recorded, but no probable value, we applied a rectangular distribution. For 25 landslides, no distribution was applied. A triangular distribution was applied for 11 events, a rectangular distribution for three, and a skewed distribution was applied for one event where the probable value was assumed to be zero, but with uncertainty. This landslide event was not included in the basic model regression analysis but is included in the Monte Carlo simulation since there is an uncertainty interval for number of exposed human in this observation. The simulated data set thus included 40,000 simulated observations.

The distributions of the original SGI data are compared to the simulated data for one, three, and four fatalities in the histograms in Fig. 1. The exposed numbers for more than four fatalities are all considered certain and therefore have no intervals. It can be noted that the distribution for one fatality is more spread out for the simulated data than for the original data of two, three, and, especially, 140 people exposed. The distribution for three fatalities is also more spread out for 155 people exposed.

Results of statistical analysis

Table 2 shows the results from the regressions using original SGI data (not simulated), where four models are estimated: the OLS models (model 1) and the negative binomial model (model 2) with and without the Verdal landslide. Results show a statistically significant positive relationship between the number of people exposed and fatalities meaning that the number of fatalities increases when more people were exposed.[2] This relationship is less strong when the outlier (the Verdal landslide) is excluded. The variable for country is not statistically significant in three of the four models. This indicates that there are no significant differences in fatalities for Norwegian and Swedish landslides, and that we can merge the data from the two countries. The year estimate is negative, but not statistically significant, meaning that we cannot conclude that the number of fatalities during the analyzed time period has decreased.

Table 3 shows the results of the regressions using data from the Monte Carlo simulations. Because 40,000 observations are included, all parameter estimates are statistically significant. Because neither a country effect nor a trend effect was found in the first estimations (Table 2), they were not taken into account. The Verdal landslide very much affects the results. In the OLS model (model 3), the risk of fatality increases linearly by 0.18 for each additional person exposed if the Verdal landslide is included; it increases only 0.02 if it is excluded. The count data models (model 4) are non-linear as can be seen from the predicted values shown graphically in Figs. 2 and 3. In Table 3 and Fig.3, the results of a model only using data for up to 20 people exposed are also shown to investigate the potential that the landslide fatality data consist of separate distributions depending on the number of persons exposed. The coefficient for number of people exposed for this model is higher than for the other models (except for 3a), indicating that the risk of fatality is higher in the sample set with 0 to 20 people exposed.

Figure 2 shows observed data, the average statistic (i.e., 0.16), and the predicted values using all observations (including the Verdal landslide) for the OLS and the negative binomial models. It illustrates that the OLS model yields a result very similar to the average. The count data model on the other hand predicts a non-linear relationship between numbers of people exposed and expected fatalities. When few people are exposed or when around 250 people are exposed, the linear and non-linear models predict the same number of fatalities. However, between these values, the linear models overestimate the number of fatalities. Note that the SGI data values shown in Fig. 2 are the numbers SGI assumed to be the most probable numbers of people exposed and not necessarily actual number of exposed humans. The simulated observations used in the estimation of the models are not shown. However, the curves are drawn from the predicted values using the models with simulated data.

Figure 3 shows observed data, the average statistic, and the predicted values excluding the outlier, the Verdal landslide, for three models applied to the Monte Carlo simulated data. Figure 3 also shows the spread of the simulated observations. However, note that it only shows the spread, not the density of the spread (cf., Fig. 1). The negative binomial model and the OLS model are similar, which means that the count data model predicts relationships that are nearly linear up to 200 exposed people. By removing the outlier, fewer fatalities are predicted. However, the graph of the negative binomial regression model only considering up to 20 people exposed shows that the risk of fatality is increasing more, compared to the models including all observations. This model

[1] More complex zero-inflated count data models were also tested. The predicted values from them were quite similar to the negative binomial model, and they are therefore not presented.

[2] The null hypotheses are that the coefficients are zero.

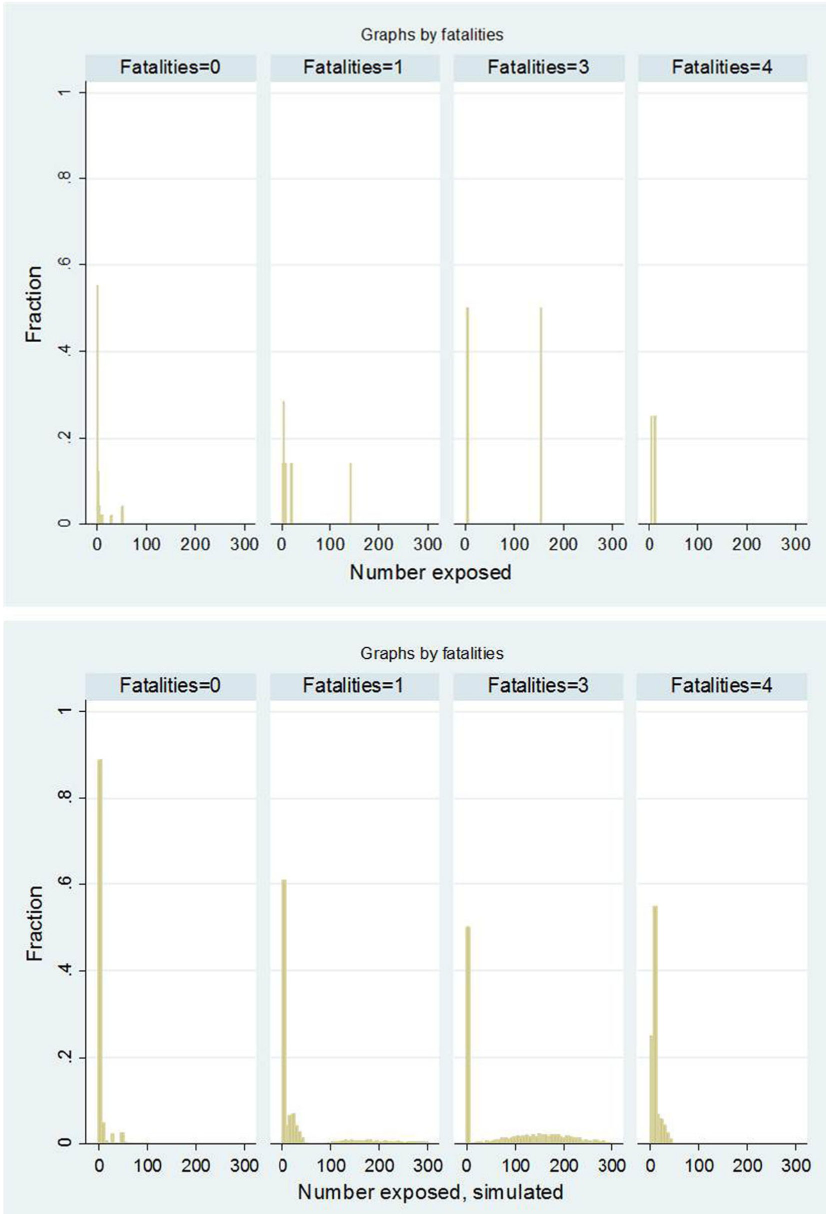

Fig. 1 Histograms of SGI data (*upper*) and simulated (*lower*) number of people exposed for 1, 3, and 4 fatalities

predicts even more fatalities than the average value used by SGI. Figure 3 therefore shows that it may be reasonable to use different fatality curves depending on the number of people exposed.

Discussion

In this study, quick clay fatality curves were derived as the relative frequency between exposure and lives lost. The results imply that loss of life increases exponentially with the size of the exposed population, but also that there might be different subsets of loss of life distributions with individual slope gradients depending on the size of the exposed population. This should be taken into account by policymakers when deciding on risk-reducing policy measures. Previously, in Sweden, a mean fatality index has been applied to risk assessments (SGI 2011). Our results imply that this approach overestimates the number of fatalities when the number of exposed individuals is between 20 and 250, underestimates it when the number of exposed individuals is high (over 250), but also underestimates it for under 20 people exposed. Probably diversified loss of life curves accounting for the size of the exposed population may be more appropriate to apply.

In our data set, individuals were exposed at their place of residence, indoors or outdoors, while working, or as a visitor in the area, and we recognize that more factors beyond exposure are likely to affect human susceptibility to quick clay landslides. Several potential factors were identified using peer-reviewed literature on landslide hazards. A functioning warning system was one such factor (Lacasse et al. 2010). Quick clay landslides, however, usually come without warning signs and therefore leave little time for

Table 2 Parameter estimates basic model. Standard errors in parenthesis

	Model 1a (incl. Verdal) OLS	Model 1b (excl. Verdal) OLS	Model 2a (incl. Verdal) Negative binomial	Model 2b (excl. Verdal) Negative binomial
Intercept β_o	52.511 (85.295)	21.330 (14.579)	18.205 (12.235)	16.878 (13.141)
Number of people exposed β_1	0.283** (0.038)	0.031** (0.010)	0.019** (0.006)	0.035* (0.021)
Norway β_2	22.709** (6.071)	1.281 (1.211)	1.855 (1.129)	4.265 (3.419)
Year β_3	−0.038 (0.043)	−0.011 (0.007)	−0.010* (0.006)	−0.011* (0.006)
Alpha			1.416** (0.701)	1.581** (0.766)
R-square	0.64	0.29		
Log-likelihood	−148.8	−77.7	−59.3	−52.8
Number of observations	39	38	39	38

*$p < 0.10$, **$p < 0.01$

emergency warning and evacuation. Despite this fact, signs had on some occasions prior to a landslide been noticed and also documented in the data set we analyzed. This was signs of gliding, creep, cracks, sinking of the ground, or small initial landslides. These signs cannot be equated to having a warning system, but could be interpreted as warning signs, if they were recognized as such. Prior experience to landslides is acknowledged as affecting human susceptibility (Zhang and Zhang 2014), and it is likely to believe that prior experience or specific knowledge would be necessary to acknowledge the "warning signs" mentioned above as a forecast for oncoming landslides. In our data set, however, only 16 slides occurred in areas previously exposed limiting the number of observations were we can assume that inhabitants had previous experience. Scandinavians ability to detect landslide threats are also affected by quick clay landslides occurring on very gentle slopes which are therefore presumed by inhabitants to be stable (Melchiorre and Tryggvason 2015). There is also reason to believe that time of day might have impacted humans preparedness and therefore affected their fatality risk. If slides occurred when inhabitants were asleep rather than in daylight, people were not to the same extent able to detect an oncoming landslide. The time of occurrence was, however, poorly documented in the data set and the uncertainty about time accuracy limited the feasibility of analyzing how this had affected human susceptibility in our cases.

Several more factors were identified as potentially affecting human susceptibility to landslides ("Landslide characteristics and methods for quantification" section) but that was too poorly

Table 3 Monte Carlo simulation. Parameter estimates basic model. Standard errors in parentheses

	Model 3a (incl. Verdal) OLS	Model 3b (excl. Verdal) OLS	Model 4a (incl. Verdal) Negative binomial	Model 4b (excl. Verdal) Negative binomial	Model 4c (max 20 no. exposed) Negative binomial
Main part					
Intercept	−0.801*** (0.078)	0.932*** (0.011)	−0.112*** (0.010)	−0.022** (0.010)	−1.079*** (0.018)
Number of people exposed (simulated)	0.178*** (0.001)	0.017*** (0.001)	0.016*** (0.0001)	0.008** (0.0001)	0.166*** (0.002)
Alpha			2.575*** (0.031)	2.457*** (0.033)	1.877*** (0.029)
R-square	0.37	0.15			
Log-likelihood	−163,296	−82,822	−64,130	−56,884	−42,263
Number of simulated observations	40,000	39,000	40,000	39,000	33,000

***$p < 0.001$

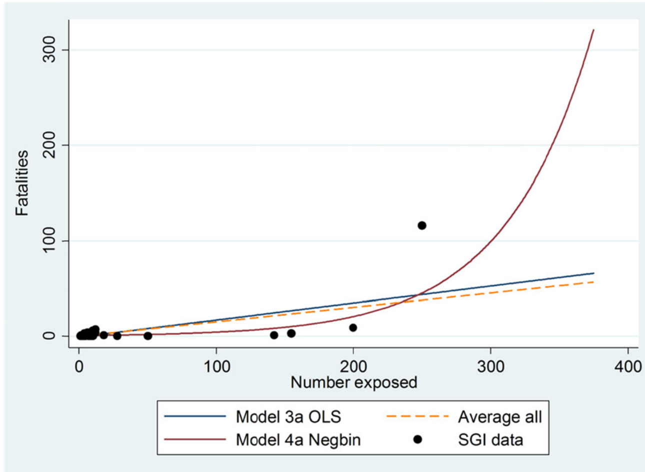

Fig. 2 Observed and predicted values. The SGI data values are the most probable number of people exposed according to the Swedish Geological Institute (SGI). The average is the average loss of life rate based on SGI's observed values of exposed persons. The predicted values (models 3a and 4a) are calculated from the estimated models using the Monte Carlo simulated data, which considers the uncertainty in number of exposed persons

documented to be quantified with the purpose of statistically measuring their effect. One reason is that damaging landslides in populated areas are low frequency events, and therefore, available data from landslides in specific areas applicable to damage analyses and damage prognoses are scarce. The quality and detail level for historical landslides also varies and can depend heavily upon the observer (Guzzetti et al. 1999; Guzzetti 2000; Guzzetti et al. 2006; Jaedicke et al. 2009; Salvati et al. 2010).

Extensive research has been performed using Italian landslide data. There are, however, some distinct differences between Italian data sets and the data set used in our study. The number of observations in the Italian data sets by far outnumbers our observations, but they do also cover a much longer time period which can raise questions concerning the applicability to present socioeconomic conditions. Further, different types of landslides are merged as opposed to the inclusion of only quick clay landslides in our study. Some Italian data sets also compile missing and injured people into a category of fatalities causing uncertainty as to the exact number of lives lost per landslide. One similarity between the data sets is that the actual number of landslides where people lost their lives is relatively few, but even in this measure, dissimilarities are distinct. We found that 27% of the 66 landslides from our data set resulted in deadly outcomes, whereas 6% was found in the Italian data by Giannecchini and D'Amato Avanzi (2012). The difference might be attributed to differences in warning and evacuation potentials between the types of landslides included. The special characteristic of quick clay landslides, that are not represented in previously derived fatality estimations, implicate that their consequences might need to be estimated separate from landslides with other characteristics, e.g., slower oncoming landslides where the land movements can be

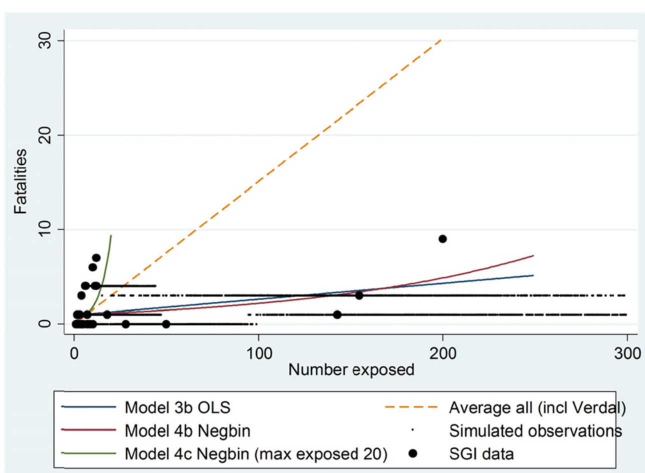

Fig. 3: Observed and predicted values excluding the Verdal slide. The SGI data values are the most probable number of people exposed according to the Swedish Geological Institute (SGI). The average is the average loss of life rate based on SGI's observed values of exposed persons. The predicted values (model 3b, 4b, and 4c) are calculated from the estimated models using the Monte Carlo simulated data, which considers the uncertainty in number of exposed persons. The spread in uncertainty is also shown by the *horizontal dots* called "simulated observations"

monitored and where warnings and evacuations can be exercised. Further, even the more well-documented Italian databases are burdened with uncertainties, e.g., uncertainties are found in poor data quality regarding the date of occurrence, number of casualties (injured, deaths, and missing people), and difficulties in differentiating landslide events from flooding events (Guzzetti 2000; Salvati et al. 2010).

Scandinavia has in modern times been relatively spared of exposure to natural hazards with large numbers of casualties. Historically, however, there have been events, e.g,. the Verdal landslide, that were devastating to communities and other events that could have been disastrous if they had occurred closer to human settlements, at another time of day, or at the present time with the present population. It is important to emphasize the effect the Verdal landslide had on the estimated functions in our study, and reflecting on whether this observation is an outlier or a low frequency observation that would recur repeatedly if the sample was to be expanded. Looking outside the sampling made by SGI, there have been incidents just as disastrous as the Verdal landslide both in Norway and Sweden. For example, in 1918 in Norrköping, Sweden, a clay landslide caused a railroad accident, killing 41. In 1726 in Verdal, Norway, a quick clay landslide killed 8. In 1648, in the Göta River valley, between 85 and 127 people were killed. These landslides are low frequency events, but they do occur and should therefore be represented when deriving loss of life estimates for application in ex-ante analysis so that the potential of experiencing more disastrous outcomes in future landslides is considered. With growing populations and urbanization, we are developing land areas more prone to quick clay landslides and thereby potentially exposing more people to landslide risks.

Conclusion

This study focused on susceptibility factors for exposed elements at risk, in this case human life. The amount of information available from historical information varied between the observations in the sample. For some quantitative information (e.g., time of day, warning signs, building characteristics, cause of death, physical ability, and age of the exposed population), the informational value of the data set was very limited. We found that potential risk factors such as country, year, and number of people exposed were the only risk factors in the sample set adequately documented to serve as input data to the statistical analysis estimating loss of life functions and the derived loss of life estimates were functions of the number of exposed persons. We do recognize that this risk factor only explain a limited part of human susceptibility when exposed to quick clay landslides slides, but it also contribute with important quantitative information to ex-ante analysis with the purpose of guiding policy decision on risk-reducing efforts. Records of historical events are one of the few sources at hand for evaluating the actual fatality risk, and despite uncertainties, they can contribute valuable information when assessing and communicating landslide risk. Concerning availability and quality of quantifiable damage and loss information in the Nordic historical records, with respect to statistical inference, the data sample set was limited. One known way of circumventing this barrier can be to transfer values derived in other studies, derived in other countries with quick clay deposits (e.g., Canada and Russia), or for other types of landslides. Based on our results, however, fatality rates obtained for other types of landslides can probably not be applied to quick clay landslide risk assessments. Future research should concentrate on quantifying risk factors that can further explain human vulnerability to quick clay landslides. The obtained results of this study also emphasize that future research regarding quick clay landslides is in need of, besides historical data, also other types of data. Such data can be obtained by performing detailed studies, e.g., surveys, investigation, in situ and laboratory tests, monitoring, analysis, and modeling, on representative cases of landslides in quick clay in order to generalize this type of studies.

Acknowledgement

The study is financially supported by Länsförsäkringar AB, Sweden. We also like to thank Lars Nyberg, Magnus Johansson, Kurt Petersen, and four anonymous reviewers for constructive comments.

Compliance with ethical standards

Disclaimer The paper has not been previously published and is not under consideration elsewhere.

References

Agrawal S, Gopalakrishnan T, Gorokhovich Y, Doocy S (2013) Risk factors for injuries in landslide and flood-affected populations in Uganda. Prehospital and Disaster Medicine 28(4):314–321. doi:10.1017/S1049023X13000356

Andersson-Sköld Y, Falemo S, Suer P, Grahn T (2011) Landslide risk and climate change—economic assessment of consequences in the Gota river valley. Proceedings of the 15th European Conference on Soil Mechanics and Geotechnical Engineering. Geotechnics of hard soils - weak rocks. Part 1 to 3

Andersson-Sköld Y, Bergman R, Johansson M, Persson E, Nyberg L (2013) Landslide risk management—a brief overview and example from Sweden of current situation and climate change. International Journal of Disaster Risk Reduction 3(1):44–61. doi:10.1016/j.ijdrr.2012.11.002

Andersson-Sköld Y, Falemo S, Trembaly M (2014) Development of methodology for quantitative landslide risk assessment—example Göta river valley. Nat Sci 6(3):130–143. doi:10.4236/ns.2014.63018

Cascini L, Ferlisi S, Vitolo E (2008) Individual and societal risk owing to landslides in the Campania region (Southern Italy). Georisk 2(3):125–140. doi:10.1080/17499510802291310

Cred (2015) The human costs of natural disasters 2015. A global perspective. Centre for research on the epidemiology of disasters. http://emdat.be/human_cost_natdis (2016–09-20)

Devoli G, Morales A, Høeg K (2007) Historical landslides in Nicaragua-collection and analysis of data. Landslides 4(1):5–18. doi:10.1007/s10346-006-0048-x

Giannecchini R, D'Amato Avanzi G (2012) Historical research as a tool in estimating hydrogeological hazard in a typical small alpine-like area: the example of the Versilia River basin (Apuan Alps, Italy). Phys Chem Earth 49:32–43. doi:10.1016/j.pce.2011.12.005

Göransson G, Norrman J, Larson M, Alén C, Rosén L (2014) A methodology for estimating risks associated with landslides of contaminated soil into rivers. Sci Total Environ 472:481–495. doi:10.1016/j.scitotenv.2013.11.013

Greene W (2008) Econometric analysis, Sixth edn. Pearson, Prentice-Hall, Upper Saddle River

Guzzetti F (2000) Landslide fatalities and the evaluation of landslide risk in Italy. Eng Geol 58(2):89–107

Guzzetti F (2016) Forecasting natural hazards, performance of scientists, ethics, and the need for transparency. Toxicol Environ Chem 98(9):1043–1059. doi:10.1080/02772248.2015.1030664

Guzzetti F, Carrara A, Cardinali M, Reichenbach P (1999) Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. Geomorphology 31(1–4):181–216

Guzzetti F, Reichenbach P, Cardinali M, Ardizzone F, Galli M (2003) The impact of landslides in the Umbria region, Central Italy. Natural Hazards and Earth System Science 3(5):469–486

Guzzetti F, Reichenbach P, Cardinali M, Galli M, Ardizzone F (2005a) Probabilistic landslide hazard assessment at the basin scale. Geomorphology 72(1–4):272–299. doi:10.1016/j.geomorph.2005.06.002

Guzzetti F, Stark CP, Salvati P (2005b) Evaluation of flood and landslide risk to the population of Italy. Environ Manag 36(1):15–36

Guzzetti F, Galli M, Reichenbach P, Ardizzone F, Cardinali M (2006) Landslide hazard assessment in the Collazzone area, Umbria, Central Italy. Natural Hazards and Earth System Science 6(1):115–131

Guzzetti F, Mondini AC, Cardinali M, Fiorucci F, Santangelo M, Chang K (2012) Landslide inventory maps: new tools for an old problem. Earth Sci Rev 112(1–2):42–66. doi:10.1016/j.earscirev.2012.02.001

Hilker N, Badoux A, Hegg C (2009) The swiss flood and landslide damage database 1972-2007. Natural Hazards and Earth System Science 9(3):913–925

Ho KKS, Chao PA, Lau TMF, de Silva S (2013) Investigation of the 20 August 2005 fatal landslide at Fu Yung Shan Tsuen, Hong Kong. Landslides 10(3):285–297. doi:10.1007/s10346-012-0332-x

Jaedicke C, Lied K, Kronholm K (2009) Integrated database for rapid mass movements in Norway. Natural Hazards and Earth System Science 9(2):469–479

Jiménez-Perálvarez JD, Irigaray C, El Hamdouni R, Chacón J (2009) Building models for automatic landslide-susceptibility analysis, mapping and validation in ArcGIS. Nat Hazards 50:571–590. doi:10.1007/s11069-008-9305-8

Jongman B, Kreibich H, Apel H, Barredo JI, Bates PD, Feyen L, Gericke A, Neal J, Aerts JCJH, Ward PJ (2012) Comparative flood damage assessment: towards a European approach. Natural hazard and earth system sciences 12(3733–3752):2012. doi:10.5194/nhess-12-3733-2012

Jonkman SN, Lentz A, Vrijling JK (2010) A general approach for the estimation of loss of life due to natural and technological disasters. Reliab Eng Syst Saf 95(11):1123–1133. doi:10.1016/j.ress.2010.06.019

JRC (2011) Safeland. Living with landslide risk in Europe: Assessment, effects of global change, and risk management strategies. 7th Framewoek Program, Cooperation Theme 6 Environment, sub-activity 6.1.3 Natural hazards

Keiler M, Zischg A, Fuchs S, Hama M, Stötter J (2005) Avalanche related damage potential- changes of persons and mobile values since the mid-twentieth century, case study Galtür. Natural Hazards and Earth System Science 5(1):49–58

Keim ME (2008) Building human resilience. The role of public health preparedness and response as an adaptation to climate change. Am J Prev Med 35(5):508–516. doi:10.1016/j.amepre.2008.08.022

Lacasse S, Nadim F, Kalsnes B (2010) Living with landslide risk. Geotechnical Engineering Journal of the SEAGS & AGSSEA Vol. 41 No.4 December 2010 ISSN 0046–5828

Long JS, Freese J (2014) Regression models for categorical dependent variables using Stata, Third edn. Stata Press, College Station, TX

Melchiorre C, Tryggvason A (2015) Application of a fast and efficient algorithm to assess landslide-prone areas in sensitive clays in Sweden. Nat Hazards Earth Syst Sci 15(12):2703–2713. doi:10.5194/nhess-15-2703-2015

MSB (2016) Swedish Civil Contigency Offic, Swedish Natural Hazards Information System. http://ndb.msb.se

Nadim F, Kjekstad O, Peduzzi P, Herold C, Jaedicke C (2006) Global landslide and avalanche hotspots. Landslides 3(2):159–173. doi:10.1007/s10346-006-0036-1

Pereira S, Zêzere JL, Quaresma ID, Bateira C (2014) Landslide incidence in the North of Portugal: analysis of a historical landslide database based on press releases and technical reports. Geomorphology 214:514–525. doi:10.1016/j.geomorph.2014.02.032

Poli S, Sterlacchini S (2007) Landslide representation strategies in susceptibility studies using weights-of-evidence modeling technique. Nat Resour Res 16(2):121–134

Roslee R, Jamaluddin TA (2012) Landslide hazard vulnerability (LHV): review of literature and a proposed new approach in landslide risk management for Malaysia. Bulletin of the Geological Society of Malaysia 58:75–88

Salas-Romero S, Malehmir A, Snowball I, Lougheed BC, Hellqvist M (2015) Erratum to: identifying landslide preconditions in Swedish quick clays—insights from integration of surface geophysical, core sample- and downhole property measurements. Landslides 1. doi:10.1007/s10346-015-0633-y

Salvati P, Bianchi C, Rossi M, Guzzetti F (2010) Societal landslide and flood risk in Italy. Natural Hazards and Earth System Science 10(3):465–483

SGI (2011) Kartläggning, exponering, sårbarhet och värdering av liv. Metodik konsekvensbedömning, GÄU- delrapport 15. Swedish Geotechnical Institute. Linköping

SGI (2012) Landslide risks in the Göta River Valley in a Changing Climate. Final report, part 1- Societal consequences. Swedish Geotechnical Institute. Linköping.

SOU (2007) Sweden facing climate change—threats and opportunities. Final report from the Swedish Commission on Climate and Vulnerability. Swedish Government Official Reports (SOU) 2007:60, Ministry of the Environment and Energy. Stockholm

Van Den Eeckhaut M, Hervás J, Jaedicke C, Malet J, Montanarella L, Nadim F (2012) Statistical modelling of Europe-wide landslide susceptibility using limited landslide inventory data. Landslides 9(3):357–369

Viscusi WK (2006) Natural disaster risks: an introduction. J Risk Uncertain 33(1–2):5–11. doi:10.1007/s11166-006-0168-7

Zhang S, Zhang LM (2014) Human vulnerability to quick shallow landslides along road: fleeing process and modeling. Landslides 11(6):1115–1129. doi:10.1007/s10346-014-0468-y

T. Grahn (✉)
Centre for Climate and Safety,
Karlstad University,
Universitetsgatan 2, 651 88, Karlstad, Sweden
e-mail: tonje.grahn@kau.se

T. Grahn
Department of Environmental and Life Sciences,
Karlstad University,
Karlstad, Sweden

H. Jaldell
Department of Economics,
Karlstad University,
Karlstad, Sweden